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(54) **Modelling an underground reservoir**

(57) A model simulating the behaviour of an underground reservoir (eg of oil) is defined on the basis of initially known geological information and available data. It enables production forecasts to be made using parameters representative of the initial data. The method essentially consists in defining one or several possible scenarios of developments during production by creating, for each of these scenarios, fictitious new production data corresponding to hypotheses about the future states of the reservoir. For each scenario considered, it is checked whether the available parameters of the simulation model can be adjusted, given the constraints of the initial geological model so that the simulation model reproduces both the measured production data and the added data. The method may be used to quantify the uncertainties regarding production forecasts by finding the min/max extremes of future production values.

FIG.1

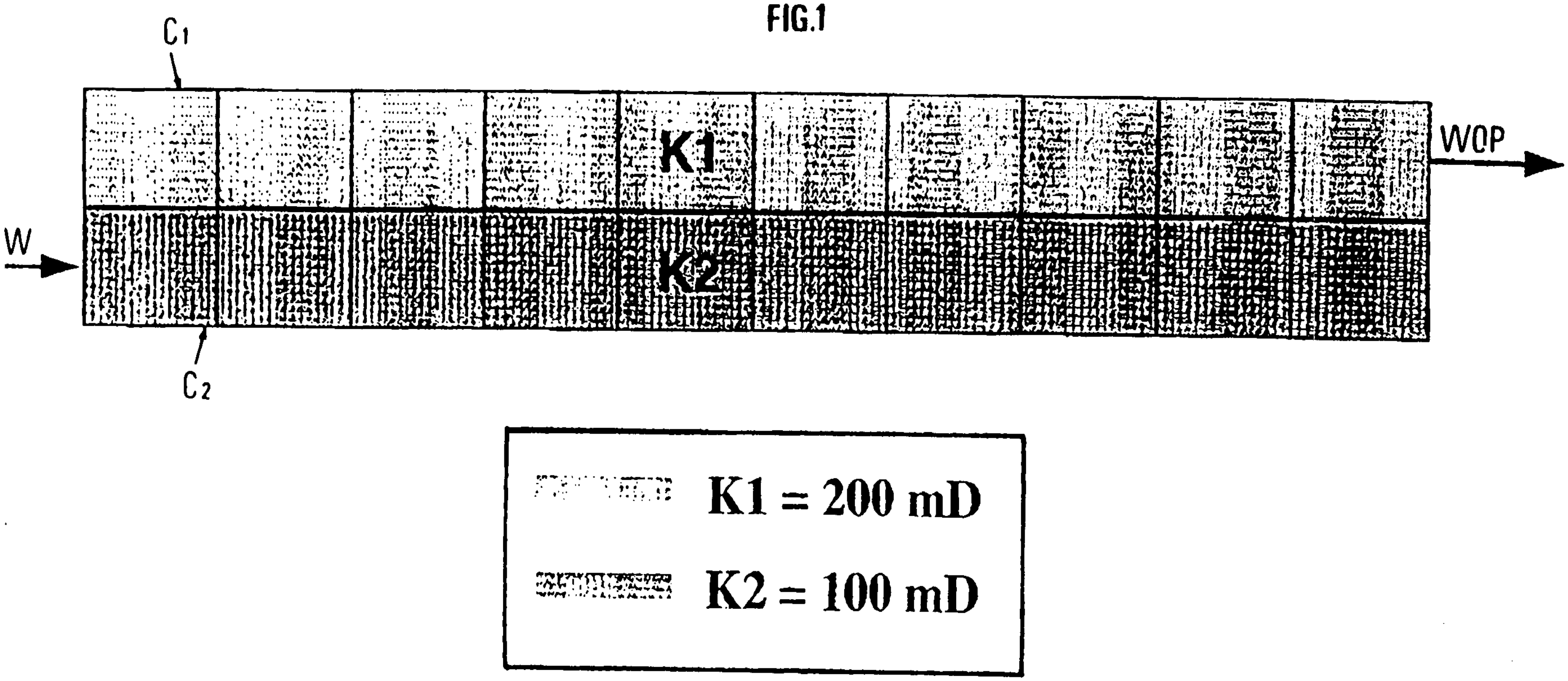


FIG.2

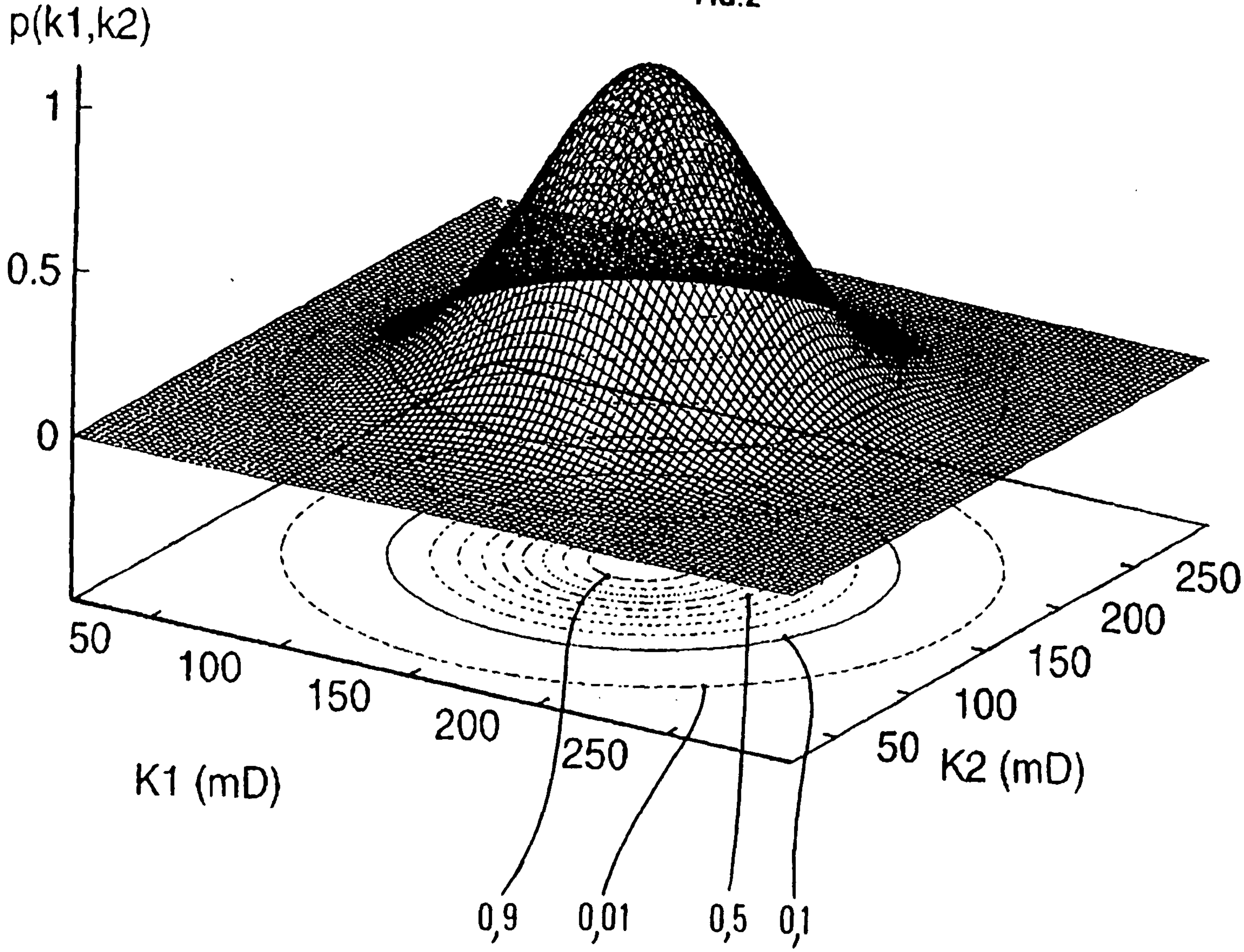

p(k1,k2)
1
0.5
0
50
100
150
200
250
K1 (mD)
50
100
150
200
250
K2 (mD)
0,9
0,01
0,5
0,1

FIG.3

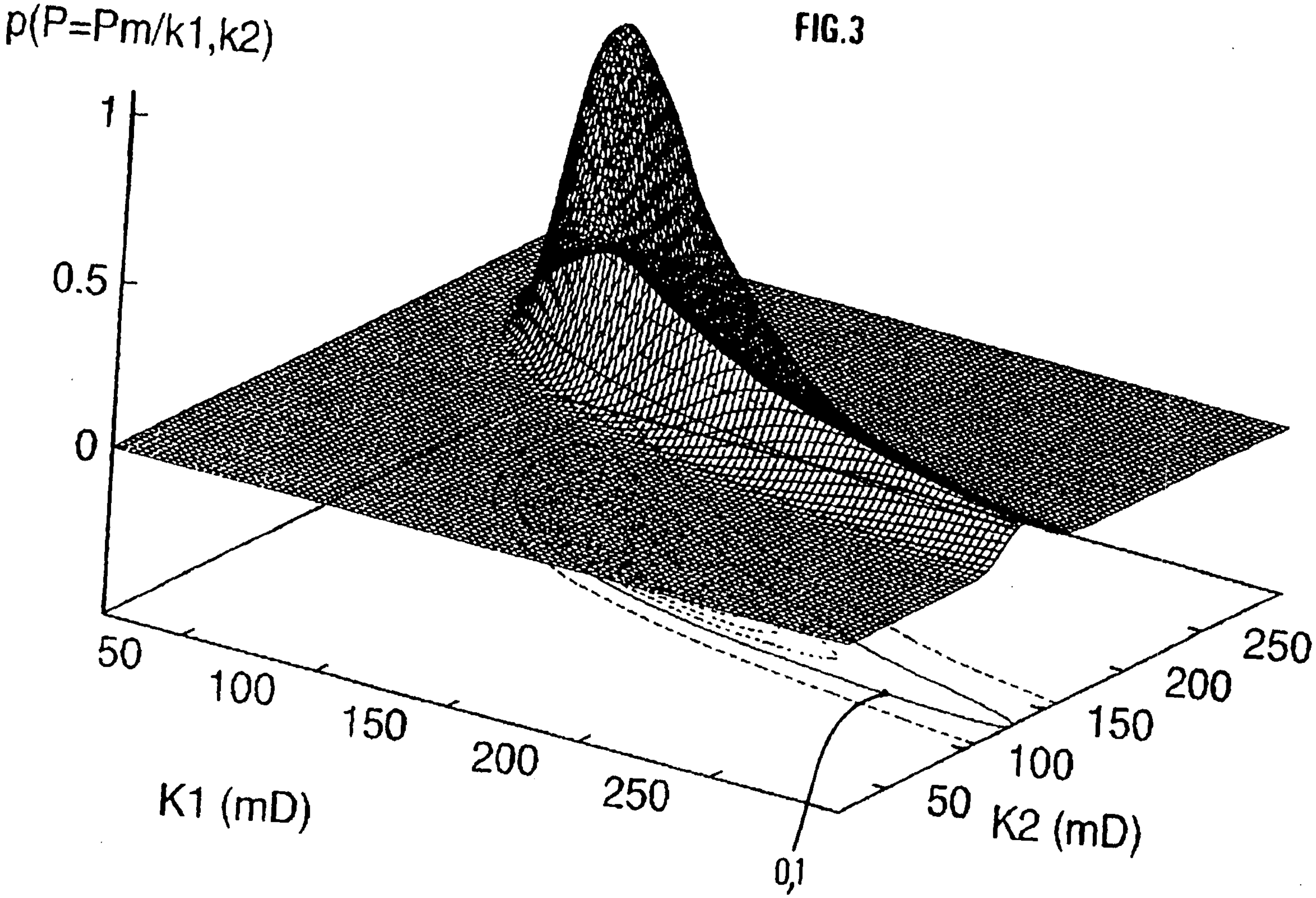
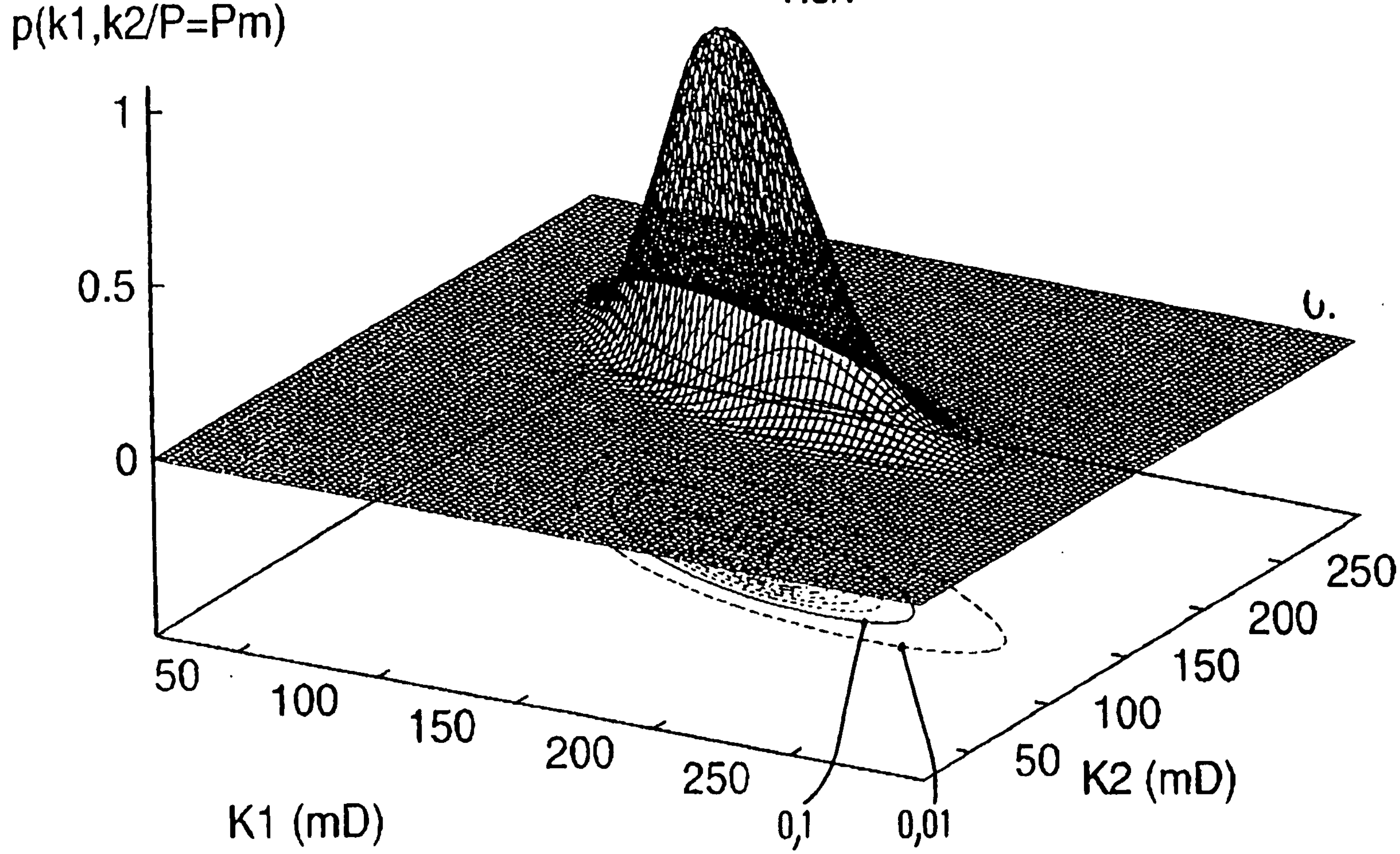

p(P=Pm/k1,k2)
1
0.5
0
50
100
150
200
250
K1 (mD)
50
100
150
200
250
K2 (mD)
0,1

FIG.4



p(k1,k2/P=Pm)
1
0.5
0
50
100
150
200
250
K1 (mD)
50
100
150
200
250
K2 (mD)
0,1
0,01

FIG.5

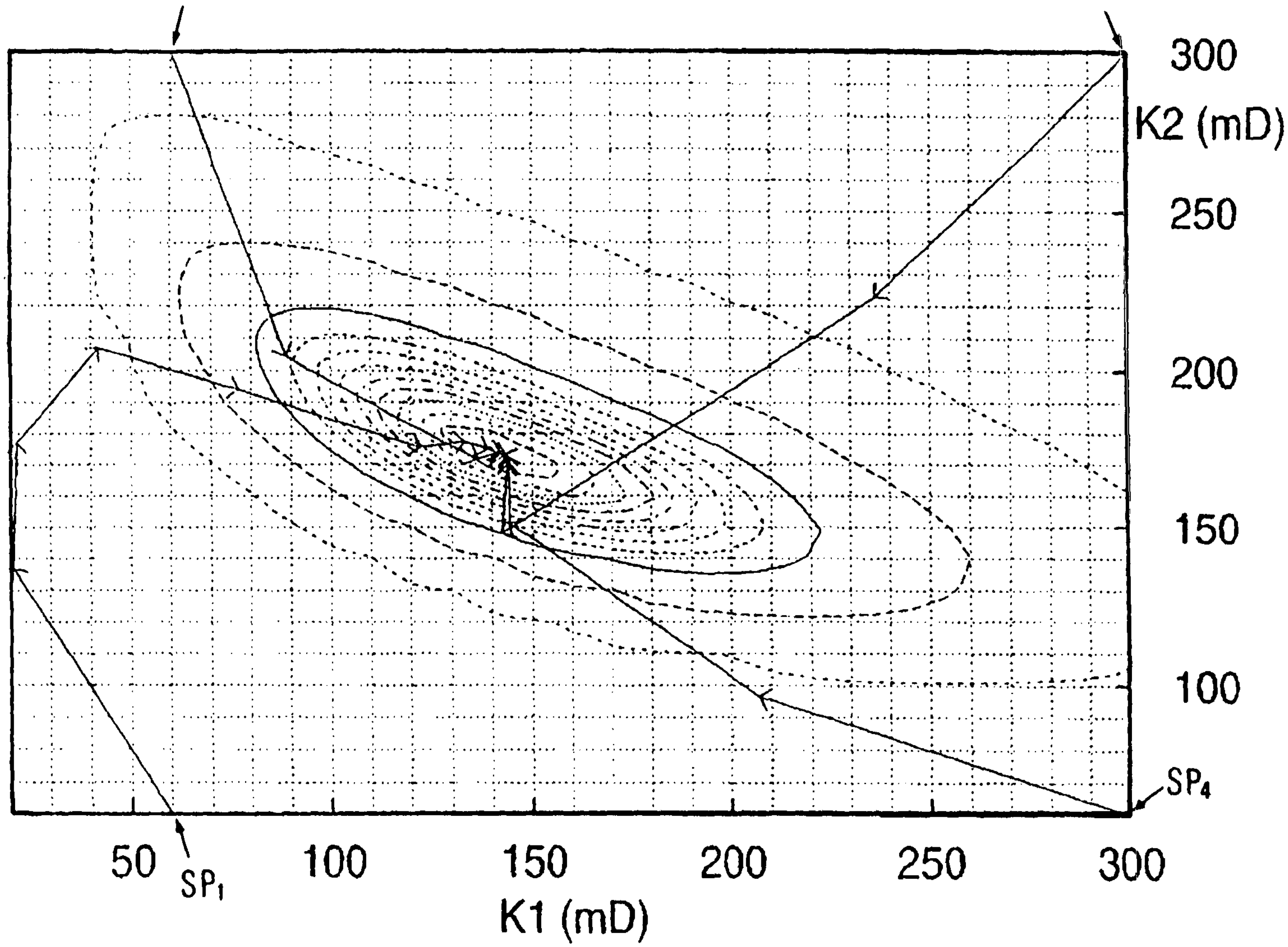
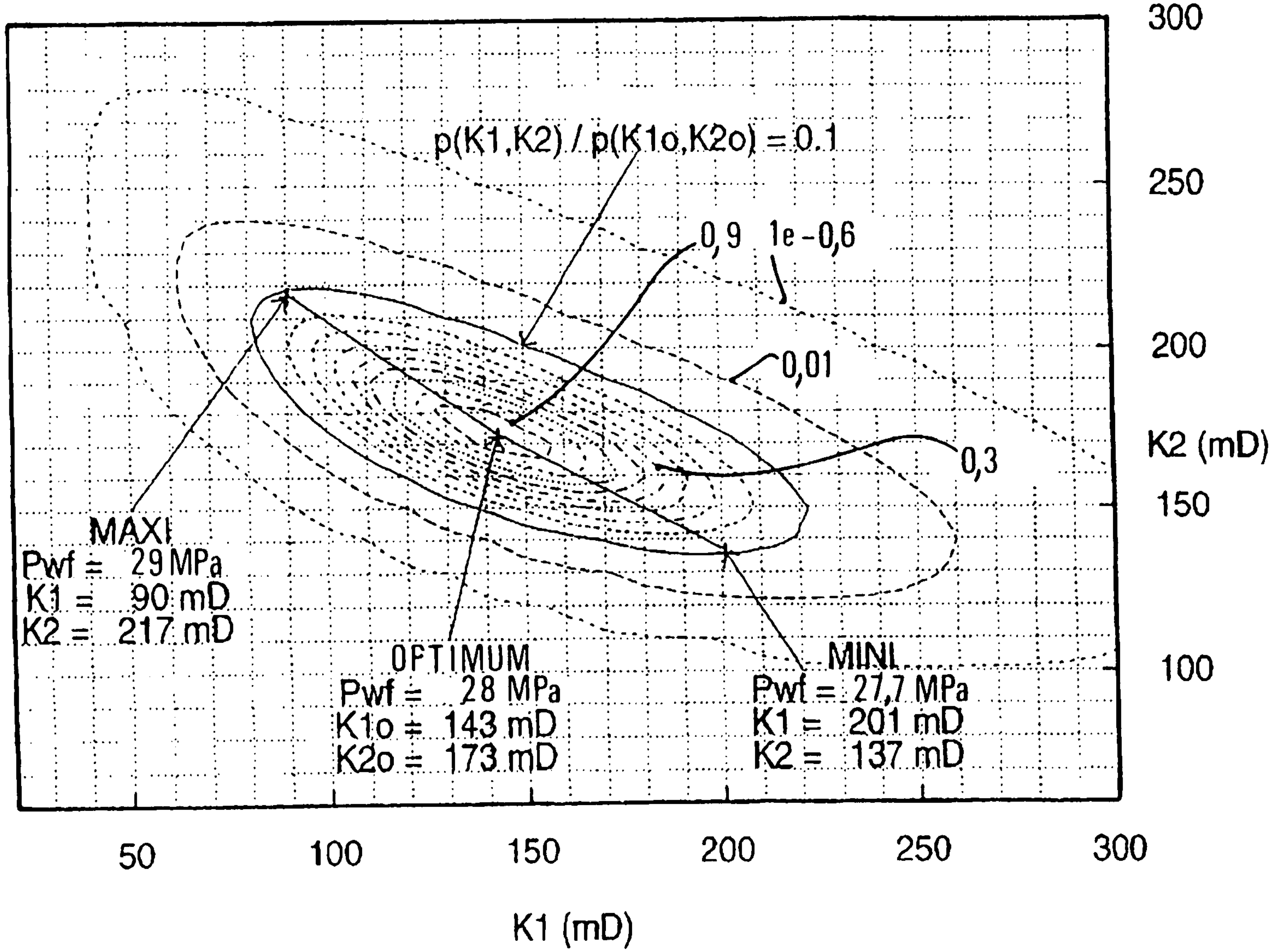

SP2
SP3
SP4
SP1
300
250
200
150
100
K2 (mD)
50
100
150
200
250
300
K1 (mD)

FIG.6



p(K1,K2) / p(K1o,K2o) = 0.1
0,9
1e-0,6
0,01
0,3
MAXI
Pwf = 29 MPa
K1 = 90 mD
K2 = 217 mD
OPTIMUM
Pwf = 28 MPa
K1o = 143 mD
K2o = 173 mD
MINI
Pwf = 27,7 MPa
K1 = 201 mD
K2 = 137 mD
300
250
200
K2 (mD)
150
100
50
100
150
200
250
300
K1 (mD)

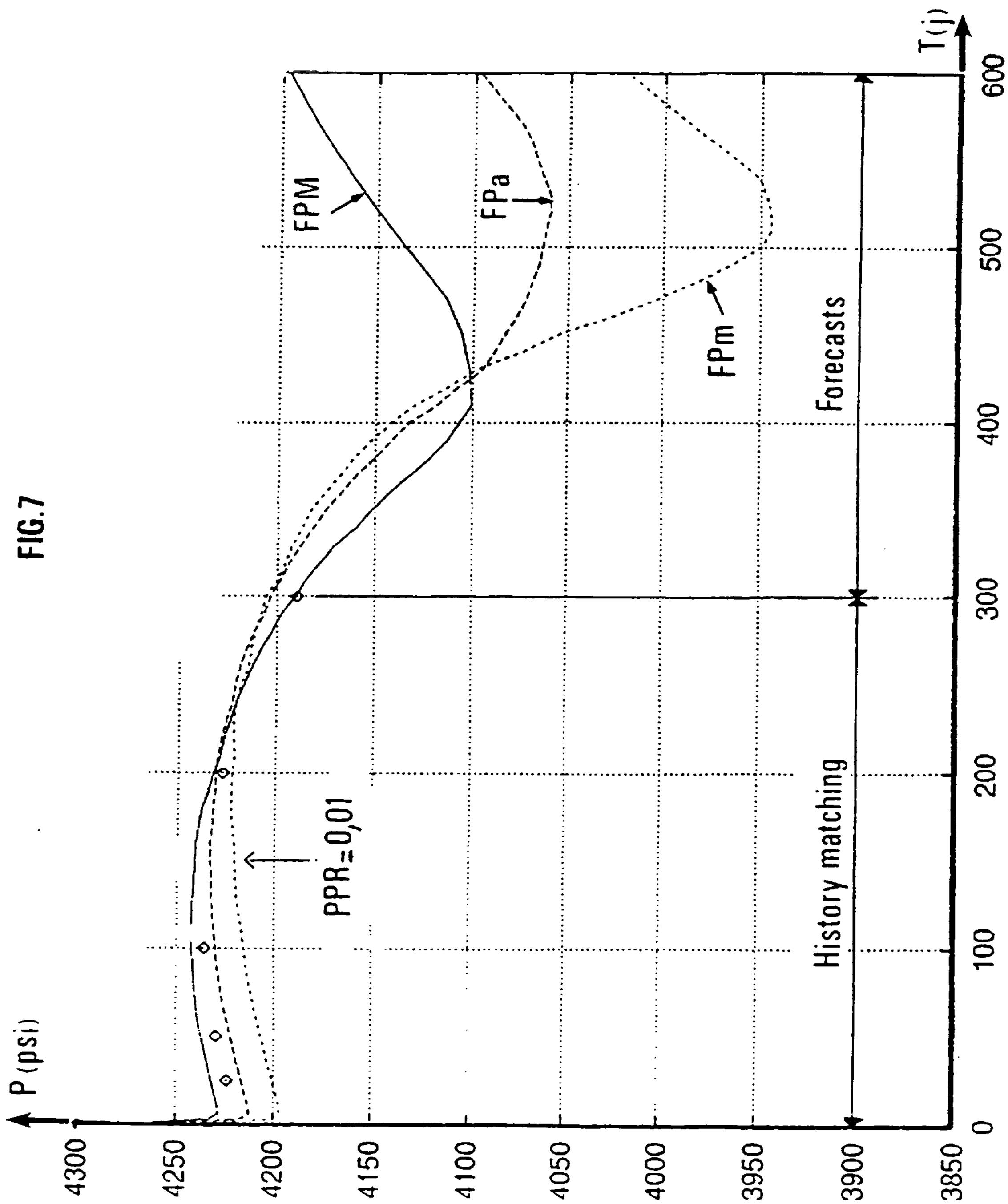

P (psi)
4300
4250
4200
4150
4100
4050
4000
3950
3900
3850
T(j)
0
100
200
300
400
500
600
FPM
FPa
FPm
PPR=0,01
History matching
Forecasts

FIG.7

2300736

METHOD FOR PREDICTING BY AN INVERSION TECHNIQUE CHANGES THAT WILL OCCUR DURING PRODUCTION IN AN UNDERGROUND RESERVOIR

The present invention relates to a method for predicting changes that will occur during production in an underground reservoir, and in a reservoir containing hydrocarbons in particular, by means of a scenario inversion technique.

BACKGROUND OF THE INVENTION

Inversion techniques are used extensively in the field of reservoir engineering. The following fields of application may be cited as examples:

- At the laboratory stage, they are used to determine various parameters representing the behaviour of rocks with respect to fluids. These parameters may be, for example: the absolute and relative permeability, capillarity curves, etc..

- Inversion techniques are also currently used to interpret well tests. In this case, the inversion parameters are, for example, the permeability of one or several facies, the geometric limits of a geological structure, coefficients pertaining to the productivity index of a well, etc..

- In studying a reservoir, inversion is used to match the response of a numerical simulator with available production measurements (or the "production history").

The parameters may be, for example, the porosity of the rocks, their absolute and relative permeabilities, the productivity indices of the wells, etc..

Technique of matching the production history of a reservoir

Inversion techniques represent a very active field of research in reservoir simulation. The process of matching a production history by adjusting parameters of a simulation model is also referred to by specialists as "history matching". It mainly consists in finding a set of parameters governing the fluid flow equations which, when integrated in a numerical simulator, enable observed or indicated data to be found again.

By way of example, the data observed in each well are mainly pressure, the composition of the fluids or the flow rate of the different phases. Any combination of these variables may also be used and in particular the water cut, the G.O.R. (Gas Oil Ratio), etc. Generally speaking, there may be many solutions to the inverse problem which will allow the production history of a reservoir to be reconstructed by a process of adjustment. It is therefore vital to incorporate what geological data is available in order to limit the range of possible solutions. By taking these initial geological data into account, the production forecasts produced by a simulation will be more realistic and more reliable.

In order to construct the initial model, any

information that is available is incorporated: raw or interpreted data, geological studies, seismic findings, etc. The physical data of a reservoir can be integrated by considering, for example:

- the structure of the sedimentological units;

- the limits of variations in petrophysical values (porosity, permeabilities, etc.) associated with litho-facies; and

- statistical data pertaining to mean values, standard deviations, spatial correlation, etc..

The process known as history matching conventionally consists of the following steps:

a) A simulation model is constructed using the initial geological data as a basis, integrating the maximum amount of data available.

b) Significant parameters of the model are selected for the inversion process by considering: data relating to the behaviour of the well as a function of these parameters, their qualitative influence on production, the initial uncertainties associated with these parameters, etc..

c) Adjustments are made using the model parameters in order to reconstruct the production history or the observed data. Having established a set of parameter values, a direct simulation enables a comparison to be made between the predicted results and the observations. The most commonly used method is a process of trial and error in which the experience of the reservoir engineer comes into play: the parameter values are adjusted on the

basis of the reservoir data and the understanding of its dynamic behaviour.

It is sometimes possible to speed up this adjustment stage by using an automatic process that enables an iterative modification of the value of the parameters so as to obtain a better match between the result of the calculation and the observation data.

The disadvantage of this conventional, largely empirical method is that the inversion process does not directly quantify the effect that the initial knowledge of the reservoir has. In practice, it is possible to match a production history whilst deviating from the admissible physical quantities. Furthermore, uncertainties in the production forecasts are not directly quantified during the inversion process. Sensitivity studies are sometimes carried out on the parameter values obtained by the adjustment process in order to ascertain their effect on the forecasts but these studies are not an integral part of the inversion process.

The process of history matching can be formalised as follows:

Physical situations are modelled using a mathematical model designated as g, which in this case is the simulator of fluid flows in the reservoir. This model is dependent on n_p parameters (vector $\underline{x}$) and time t. The physical situations modelled can then be written in the form $d = g(\underline{x},t)$. If $\underline{d}_m$ represents a set of n_m observations corresponding to the measurements of d at

different times t_i, then the following conditions can be formulated so that the model reproduces the observations :

$$\underline{d}_m = \{g(\underline{x},t_i), i = 1,n_m\}$$

In order to define a criterion for adapting the model to the observations, a function can be defined in the conventional manner of the "least squares", expressed, for example, as follows:

$$F_m(\underline{x}) = 1/2\sum i=1,n_m\{(di-g(\underline{x},t_i))^2\}$$

The parameters retained are those which minimise the function $F_m(\underline{x})$ by taking account of the constraints imposed on the parameters.

It should be noted that the quality of the predictions produced by this procedure may sometimes be open to question for two main reasons. The first is that the initial or a priori knowledge of the reservoir is not quantified, which means that it may disappear during the minimisation processes. The second is that there may be several solutions which minimise the function. This being the case, in order to improve the quality of the predictions, it is important to take account of any information that is available about the geological model as well as any statistics that will characterise these parameters during the adjustment process.

Bayesian technique of inversion of a simulation model

In order to take account of this initial information, an inversion formalism known to specialists as "Bayesian Inversion" can be used. This is described, for example,

by:

Floris F.J.T. et al, in "Flow Constrained Reservoir Characterization using Bayesian Inversion", 4th ECMOR, Norway, 7-10 June 1994.

This formalism, which is known to specialists, allows account to be taken of a priori data pertaining to the parameters in the form of probabilistic models, errors made in the measurements along with their relative probabilities as well as errors caused modelling flows using a numerical simulator. Given the calculating means currently in use, Bayesian formalism is unfortunately very costly in terms of calculating time and is not very practical where an entire field is under consideration since it requires the flow simulator to "sweep" all the possible parameters in order to evaluate the probability of each solution.

The underlying principle of this Bayesian inversion as applied to flow simulation in a reservoir is to modify the initial geological model by using the production data in order to improve the quality of this initial model. The main steps are:

a) Constructing an initial geological model.

This is an "a priori" model of the probabilistic type. The reservoir is described on the basis of a set of parameters together with their associated probability density functions p(x). Mean values for these a priori parameters (designated as $\underline{x}_a$ and standard deviations (designated as σx) can be used to model this probability density function, designated as pdf. With Gaussian type

uncertainties, modelled by a covariance operator designated as Cx, the a priori function pdf can be expressed as:

$$p(\underline{x}) = Cte\ \exp\{-(\underline{x}_a - \underline{x})^T C_x^{-1} (\underline{x}_a - \underline{x})\}$$

In order to express this a priori data in an objective function, a new term, designated as $F_x(\underline{x})$, has to be added to the previously defined term $F_m(\underline{x})$, and can be expressed as follows in the case of Gaussian uncertainties:

$$F_x(\underline{x}):1/2\{-(\underline{x}_a - \underline{x})^T C_x^{-1} (\underline{x}a - \underline{x})$$

b) Using the observed data:

the observation data are used to calculate the a posteriori probability density function p(x/d=dm) in accordance with the Bayes rule:

$$p(\underline{x}/\underline{d}=\underline{d}_m) = (p(\underline{d}=\underline{d}_m/\underline{x}).p(x))/p(\underline{d}=\underline{d}_m),$$

where $p(\underline{d}=\underline{d}_m/\underline{x})$ is the likelihood function which quantifies the differences between the observed values $\underline{d}_m$ and the calculated values $\underline{d}$ for a given set of parameters $\underline{x}$. If the uncertainties about the measurements and about the model are Gaussian and are modelled by a covariance operator C_m, this likelihood function can be expressed as follows:

$$p(\underline{d}=\underline{d}_m/\underline{x}) = Cte\ \exp\{-(\underline{d}_m-\underline{d})^T C_m^{-1}(\underline{d}_m-\underline{d})\}$$

In order to obtain a statistical interpretation in terms of probability densities pdf, it is necessary in practice to determine the a posteriori function for the full range of parameters. If the maximum a posteriori probability only is considered, the parameters corresponding to this optimum are those which minimise

the objective function $F=F_m(\underline{x}) + F_x(\underline{x})$.

To sum up, for each set of parameters, the associated probability $p(\underline{x})$ is increased if the response of the model $g(\underline{x},t)$ provides values close to those observed $\underline{d}_m$, i.e. when the likelihood function $p(\underline{d}=\underline{d}_m/\underline{x})$ is high.

The conventional method of history matching and the Bayesian inversion technique, mentioned and discussed above, are used to adapt a simulation model to actual measurable data. The major disadvantages of the first method are the possibility of losing a part of the initial information and a high degree of uncertainty as to the reliability of the predictions. Bayesian formalism allows the uncertainties pertaining to the geological parameters to be characterised more accurately and takes account of the a priori geological data. However, inversion of the Bayesian type is, in practice, very difficult to apply to real case studies, the cost incurred by the number of simulations needed being prohibitive.

Furthermore, these methods are not intended as a response to the problem of quantifying uncertainties linked to production forecasts. Conventionally, the uncertainties are estimated a posteriori, after the inversion phase. Forecasting uncertainties, however, is crucial in drawing up a reservoir development programme, for which economic criteria based on the reliability of the forecast are required.

The method of the invention allows the quantification of production uncertainties to be directly integrated in

the inversion process in a same procedure. The objective of this method is both to:

- enable optimum matching of a simulation model to a production history by taking account of all the a priori information, and

- enable uncertainties about production forecasts to be directly quantified and test hypotheses on the evolution of these production forecasts.

The method enables a reservoir engineer to test production forecast scenarios and thus better validate his model against the initially known data of the reservoir. Consequently, it is possible to verify whether a production scenario is compatible with the geological data or quantify the production uncertainties inherent in the geological uncertainties.

Forecasts of the likely evolution of production of an underground zone containing fluids, such as a hydrocarbon reservoir, can be produced by the method of the invention by carrying out the following steps:

a) In a conventional initial step, already described in connection with the commonly used inversion methods, an initial geological model defined by a set of parameters is constructed by integrating all the available data. At this stage, conventional inversion methods can be used to determine the values of parameters which will allow the response of the model to be adjusted to the production history;

b) One or several possible development scenarios for production are defined. For each of these scenarios,

fictitious data are added to the observed data (or "actual" data) at given instants in the future corresponding to these hypotheses;

c) For each scenario, the parameters of the said model are adjusted to reconstruct both the actual measurements derived from the production history and the data added at future times and an inversion procedure is applied in order to obtain a new set of parameters $\underline{x}$ for each scenario, which characterise a modified geological model and correspond to the hypotheses of the scenario;

d) Direct simulations are then produced for each of these modified geological models in order to establish new production forecasts.

It is possible to use conventional procedures in each inversion phase. However, it is of advantage to use an automatic inversion procedure in which an objective function is minimised by incorporating the initial data associated with the geological model and to use the Bayesian formalism to take account of these initial data.

To this end, the method may include a combination of an inversion formalism of the conventional Bayesian type and an optimisation algorithm based on the use of the gradients method, enabling the derivatives of the production forecasts to be obtained in relation to the parameters. By combining this method with a Bayesian formalism, it is possible to reduce the number of operations needed to obtain the optimum probability by a considerable degree, since the advantages of the Bayesian inversion (which takes account of the initial data) are

combined with the efficiency of inversion algorithms using gradients.

Consequently, the method of the invention basically makes it possible:

- for the uncertainty inherent in the geological model to be interpreted by quantifying the uncertainty relating to production,

- to test whether the predicted hypotheses are compatible with the data known about the reservoir from the outset.

Finally, combining Bayesian formalism with a gradients method means that this method can be operated on the basis of more effective algorithms than those previously used.

Other characteristics and advantages of the method of the invention will become clear from the following description of embodiments and validation tests, given by way of non-limitative examples, and from the attached drawings, in which:

- Fig. 1 is a diagram of a geological model made up of two layers, C1, C2, in vertical section;

- Fig. 2 shows the a priori probability density p(k1, k2) ("a priori pdf") characterising the initial geological model as a function of permeabilities K1, K2 of the two layers C1, C2 of the model of Fig. 1;

- Fig. 3 shows how the resemblance or likelihood function p(P=Pm/K1, K2) varies, characterising the probability of a simulation as a function of these same parameters;

- Fig. 4 shows the variation in the a priori probability density p(k1, k2/P-Pm) ("a posteriori pdf") obtained by Bayesian inversion.

- Fig. 5 shows the automatic adjustment process, based on combining Bayesian formalism with the gradients method, which allows the optimum of the a posteriori probability density to be obtained. The process is illustrated starting from four different starting points SP1, SP2, SP3, SP4;

- Fig. 6 shows, in the parameter space, the geological models obtained for an optimum prediction, a maximum prediction and a minimum prediction; and

- Fig. 7 shows the curve FPa representing the predicted variations over time of the bottom hole pressure in the production well, surrounded by the curves FPM and FPm corresponding to the maximum and minimum forecasts respectively.

DESCRIPTION OF THE METHOD

The method of adjusting production scenarios as proposed by the invention consists of the following steps:

1) Firstly, an initial geological model of the reservoir zone under study is constructed, incorporating all the information available beforehand. An inversion method of a known type and in particular the Bayesian inversion process described above can be used to carry out a first production history match. The adjusted model

can be used to obtain a mean prediction.

2) Once this initial model has been established, one or several possible scenarios of developments during the course of production are defined. These scenarios correspond to hypotheses pertaining to how production will develop over time. Fictitious data corresponding to given future instants are added for each of these scenarios. These fictitious data can relate to a possible water inflow at a given time, for example, or hypotheses relating to oil recovery.

3) The parameters of the initial model are adjusted to obtain a match with both the production history (observed data) and the additional data relating to the production hypotheses. A conventional inversion process is used for each scenario in order to obtain a new geological model, defined by a new set of parameters $\underline{x}$ and corresponding to the previous hypotheses.

4) The probability of each scenario created is verified directly using an inversion formalism of the Bayesian type, for example, with the value of the a posteriori probability density function.

5) The models obtained are used to produce direct simulations for each of these scenarios, so that new production forecasts can be produced.

Several situations might arise. By considering the choice of parameters and the constraints on the geological model, a set of parameter values can be found which will enable the measured and added data to be reproduced. This information can be very useful to the

reservoir engineer. If, for example, the aim of the scenario created is to test whether a premature inflow of water could occur in a given well and if the process of evaluating the scenario produces a set of physically admissible parameter values, the reservoir engineer will be in a position to take decisions about how the reservoir will be developed so that this risk can be prevented or he may decide to carry out new measurements to check whether the risk is real.

Another conceivable situation is where the adjustment procedure can be applied to the scenario but only at the expense of considerable distortion to the initial geological model. The reservoir engineer can then be confident in his forecasts and be assured that the occurrence of such an event is highly unlikely. In the same hypothesis of preventing a premature inflow of water, he can regard the risk as being very low before a given period of time has elapsed.

Another area where the method can be applied is for directly quantifying production uncertainties by finding extreme scenarios. This application will be described below.

Comparison of a pessimistic scenario and an optimistic scenario as a means of assessing uncertainty

The objective function F mentioned above in connection with conventional inversion techniques uses the information obtained from the time the reservoir was

placed under production to the present. Several sets of parameter values may provide solutions which will minimise the objective function. Dealing with uncertainties in the forecasting process from the present instant (t=tt) of the production period to a future instant (t=tf) may be a question of selecting from several possible solutions the set of parameter values which will give the "best" scenario and that which will give the "worst". The scenarios can be defined using a criterion that is dependent on production strategy during the forecast period under consideration, for example between tt and tf. The criterion may be the total quantity of oil produced, for example, the total maximum flow rate, the instant of water inflow, the G.O.R., etc..

The best way of resolving this problem is to apply the method of the invention to two optimisation problems where the first corresponds to the "best" scenario and the second the "worst".

In the first instance, a set of parameters is found which gives both a good match with the production history of the reservoir (i.e. the set of parameters which minimises Fm + Fx) and a maximum value for the criterion:

$$\mathrm{Min}(Fm + Fx) + \mathrm{Max}(\mathrm{Criterion}).$$

In the second instance, the set of parameters is found which combines a good history match with a minimum value of the criterion:

$$\mathrm{Min}(Fm + Fx) + \mathrm{Min}(\mathrm{Criterion}).$$

Formalism of the method:

A future instant tf is selected and new data are added to the existing production data. Each of the new values corresponds to a predicted production scenario. The predicted min/max production scenarios at this future instant tf are determined.

To this end, the parameter values are adjusted in order to obtain an optimum match of the production history whilst distorting the production forecast curve so that the minimum or maximum is attained at the future time t=tf. An iso-probability constraint is imposed in order to check the feasibility of each scenario.

The problem is reduced to a problem of optimisation with non-linear constraints. The objective function used is

$$F = F_m + F_x + F_f$$

$F_m + F_x$ represents the previous objective function incorporating the a priori data. F_f can be expressed as:

$$F_f = 1/2(d_f - g(\underline{x},t_f))^2; \quad \text{where}$$

d_f represents the additional data at the time t_f; and

$g(\underline{x},t_f)$ represents the production forecasts at the time t_f.

F_f is an additional constraint used to obtain the min/max scenarios. The added data d_f are adjusted to satisfy the following two constraints:

1) $F_m + F_x \leq F_{hmc}$, where F_{hmc} is a given criterion measuring the quality or the admissible standard of the production history match:

2) $g(\underline{x},t_f)$ represents a maximum or minimum forecast.

The first constraint is equivalent to a constraint of relative probability pertaining to an a posteriori probability density function by reference to the maximum probability. A ratio of a posteriori probability (ppr) is given:

$$ppr = p(\underline{x}/\underline{d}-\underline{d}_m)/p(\underline{x}\infty/\underline{d}=\underline{d}_m),$$

where $x\infty$ is the optimum position (parameter values corresponding to the maximum probability). The admissible standard criterion of the history match is then:

$$F_{hmc} = F_m(\underline{x}\infty) + F_x(\underline{x}\infty) - \log(ppr)$$

A quadratic convergence optimisation algorithm, such as the Gauss-Newton algorithm known to specialists, can be used to minimise the objective function ($F=F_m + Fx + Ff$).

This algorithm can be used to carry out an automatic process of adjustment to the history, finding the maximum or the minimum of the production forecasts simultaneously.

It can be of advantage to use a multi-purpose reservoir simulator to carry out this procedure, bringing the gradients method into play. By using the gradients method, the sensitivity of the model to the inversion parameters is in effect obtained directly. This method is well know to specialists and has been described, for example, by:

Anterion F. et al., "Use of parameter gradients for reservoir history matching", SPE 18433, Houston, TX, February 6-8, 1989.

When using gradient values, the optimisation algorithm is very effective in dealing with the problem in the context of a global iterative method, incorporating the search for extreme scenarios and optimum matching of the production history. The method of the invention allows an inversion algorithm to be used that combines the advantages of Bayesian formalism and the efficiency of optimisation algorithms based on the use of gradients. The method enabling the Bayesian formalism to be combined with the gradients method is described below.

Modified Bayesian type inversion formalism

When carrying out the inversion procedures, it can be of advantage to use a specific inversion method derived from the Bayesian type of formalism, which allows a direct and much faster search than conventional formalism to find the optimum position of the a posteriori probability density function.

The objective is achieved by defining a function to be optimised and by combining the Bayesian formalism with the gradients method. The initial information associated with the geological model can be incorporated in this function to be minimised. In addition, by making certain assumptions, it is possible to obtain an approximation of the a posteriori probability density around this optimal solution. To include this initial knowledge in the function to be minimised (designated as F), a new term

which is dependent on the difference between a given a priori average $\underline{x}_a$ and the value $\underline{x}$ of the following parameters, is introduced:

$$F = (F_m + F_x)/2, \text{ with}$$

$$F_m = (\underline{d}_m - \underline{d})^T C_m^{-1} (\underline{d}_m - \underline{d}), \text{ and}$$

$$F_x = (\underline{x}_a - \underline{x})^T C_x^{-1} (\underline{x}_a - \underline{x}).$$

Covariance operators are introduced to model the Gaussian uncertainties on the measurements (matrix C_m) and the a priori probability density on the parameters (matrix C_x0.

The proposed formula is an extension of the conventional objective function of least squares. There is a direct link between the objective function and the Bayes rule. The a posteriori probability density function can be expressed in the form:

$$p(\underline{x}/\underline{d}-\underline{d}_m) = Cte.\exp(-F) = Cte\{\exp(-F_m).\exp(-F_x)\}, \text{ with}$$

$$p(\underline{d}=\underline{d}_m/\underline{x} = Cte_1 \{\exp(-F_m)\}$$

$$p(\underline{x}) = Cte_2 \{\exp(-F_x)\}.$$

The parameters obtained for the maximum of the a posteriori probability density function, denoted as $\underline{x}\infty$, can therefore be considered to be those which minimise the objective function F. This correspondence is well known to those specialised in inversion. The modified procedure differs in that:

- it uses the gradients method to minimise the objective function, which, in accordance with the invention, makes it possible to obtain extreme production scenarios with an iso-probability criterion; and in that

- it uses the gradients method combined with Bayesian

formalism to obtain, by linearisation, an approximation of the a posteriori probability density in the vicinity of the optimum. In practice, this method is able to meet satisfactorily the constraints of a posteriori iso-probability in the inversion algorithms.

Once convergence has been reached in the optimisation procedure and the optimal values $\underline{x}_{\infty}$ have been found using the gradients method, assuming that the a posteriori probability density is locally Gaussian, it is modelled by an a posteriori covariance operator. Calculation of this covariance operator gives an approximation of the "a posteriori probability density" function.

Experimental example

The validity of the method of the invention was tested on a synthetic experimental case, set out below, which demonstrates clearly the improvement attained by combining inversion formalism of the Bayesian type with a gradient method and the possibility of quantifying uncertainties about the predictions by researching extreme scenarios.

Having defined a synthetic geological representation, a numerical simulation was performed to obtain synthetic production data using an industrial reservoir simulator of the usual type.

An initial geological representation was chosen, representing the information available about the reservoir beforehand. The geological model in this case

is a vertical section having two layers (Fig. 1) C1, C2, 7.5 m in height and 100 m thick, with constant horizontal permeabilities K1, K2 of 200 mD and 100 mD respectively. The simulation grid is made up of ten cells for each layer in the horizontal direction and the total length is 500 m.

Water is injected, on the left-hand side of the reservoir, into the lower section and a total liquid flow rate (water + oil) is produced on the right-hand side of the upper layer. The same volume flow rate (200 m^3/j or 1250Bl/j) is imposed on the injector and on the producing well in order to maintain the average pressure and prevent the oil pressure from falling below the bubble point.

The fluids that were initially present in the reservoir form a petroliferous reservoir containing 12% of irreducible water. A numerical simulation is conducted during a production period of 600 days. During an initial period, (from t = 0 to t = 300 days), only the oil phase is produced. The water does not reach the producing well until after a period of about 300 days. The volume of water produced increased during the final period: 10% of water at t = 380 days and 77.7% of water at the end of the simulation (t = 600 days).

Synthetic measurements were produced using the results of this reference simulation. Only the first production period from t = 0 to t = 300 days) was used: in order to conserve a greater degree of uncertainty with respect to the initial characterisation of the reservoir,

it was assumed that the time at which a water inflow occurred was unknown. The measurement selected was down hole pressure in the producing well with five values observed between 25 and 300 days.

An overall uncertainty range was selected to describe both the measurement uncertainties and the numerical simulation errors. These uncertainties were modelled using the Gaussian probability densities centred on the results of the reference simulation and with σ=138 kPa (20psi) for the standard deviations.

These standard deviations were implemented in the objective function in the diagonal terms of the covariance operator C_m relating to the measurements. If one considers the first term of the objective function F_m which quantifies the variance between the observations d_m (in this case the down hole pressure) and the response of the simulation g(x,t), the diagonal terms of C_m^{-1} are equal to $1/\sigma_m^2$.

Defining the a priori geological model

It is assumed that the geological reference model is unknown and that some geological information is available beforehand. On a hypothetical basis, the geometry is considered to be well characterised, that the horizontal permeabilities assigned to each layer are unknown and that a priori information about these permeabilities is available but with a given margin of uncertainty.

The two horizontal permeabilities have been selected

as being the parameters to be subjected to inversion. The a priori information available is modelled by means of Gaussian uncertainties (Fig. 2). The variance between the a priori permeabilities x_a and the parameters x is quantified in the second term of the objective function F_x. The standard deviations of the parameters σ_x are incorporated in the covariance operator C_x in the same way as for modelling the measurement errors: the diagonal terms of C_x^{-1} are equal to $1/\sigma_x^2$. The extra-diagonal terms are zero for this example, which means that the a priori data pertaining to a possible correlation between the two parameters were not incorporated.

The numerical values selected a priori are set out in table 1 below:

Table 1: A priori geological model

	A priori value	Standard deviation	Value of the reference case
K1 (upper layer)	160 mD	40 mD	200 mD
K2 (lower layer)	160 mD	40 mD	100 mD

Comparison of different inversion methods for the test case

A) Automatic history matching method

Firstly, a conventional history matching method combined with an automatic optimisation algorithm is applied. In this initial approach, the geological data

available beforehand are used only to select the starting point of the process. The objective function to be minimised incorporates only the first term F_m and does not take account of the a priori model.

The initial parameters are fixed at 160 mD (a priori values). The automatic matching procedure based on a gradient method and the conventional Gauss-Newton optimisation algorithm is used. In this case, the sensitivity of the down hole pressure in the producing well to the permeability values is obtained by the gradients method.

Because synthetic measurements produced by the numerical simulator are used, the adapted model obtained in this way is very close to the reference case. Only five simulations are needed to obtain the position of the function minimum. The optimisation process is summarised, from the starting point to an optimum, in table 2 below:

Table 2: Automatic optimisation process for history matching

Iteration Number	K1	K2	Fm
0	160 mD	160 mD	0.799
1	172.8 mD	133.6 mD	0.407
2	193.4 mD	104.9 mD	0.042
3	200.8 mD	99.1 mD	0.0008
4	200.5 mD	99.9 mD	0.0003

Use of the Bayesian type inversion formalism

By using the Bayesian inversion method, the a posteriori probability density is obtained, mapped over the entire parameter space. In this instance, the information available beforehand (Fig. 2) is taken into account in this a posteriori probability density by combining it with the likelihood function (Fig. 3) calculated for each group of parameters.

The parameter space has been mapped with a large range of permeabilities, from 20 mD to 300 mD, with 35 values for each parameter (the total number of numerical simulations will be $35^2 = 1225$ operations). It is of advantage of have a full map of the a posteriori likelihood function in that it enables numerous data about the simulation behaviour to be obtained. If we look at the graphical representation of the function (Fig. 4), the following points can be noted:

- only one optimum is clearly identified, located at 143 mD (permeability of the upper layer) and at 173 mD (permeability of the lower layer). The maximum value of the a posteriori probability density is $1.48.10^{-7}$;

- it was possible to obtain a better characterisation of the geological model with a lesser degree of uncertainty with regard to the parameters (compared with the a priori probability density function of Fig. 2);

- a correlation is established between the two parameters; the shape of the surface is not symmetrical around the optimum but is distorted on an axis of

correlation.

On the other hand, integration of the surface makes it possible to calculate the a posteriori statistical parameters with regard to the parameters.

Tables 4 and 5 below show the standard a posteriori deviations compared with the initial data:

Table 4: Initial and a posteriori parameters

	Initial	A posteriori
K1	160 mD	143 mD
K2	160 mD	173 mD

Table 5: Initial and a posteriori standard deviations

	Initial	A posteriori
K1	40 mD	32.8 mD
K2	40 mD	19.0 mD

Using Bayesian type formalism combined with the gradients method

This modified inversion procedure combining, as we have seen, inversion formalism of the Bayesian type with a gradients method was applied to the experimental case.

The optimisation algorithm is applied to find the optimum of the a posteriori probability density function directly. Four different starting points were used to cover the initial range of uncertainties. For each optimisation process, the optimum is reached with between 4 and 7 iterations (Fig. 5). The proposed statistical analysis is applied in the area around the optimum. The results obtained are compared with the conventional

Bayesian inversion method in table 6 below:

Table 6: Comparative results obtained with conventional Bayesian inversion and with the modified inversion

	Bayesian inversion	Modified inversion
Number of operations	1225	20
Optimum (en mD)	K1=143	K1=143.2
	K2=173	K2=172.9
Standard deviations (in mD)	K1=32.8	K1=31.4
	K2=19.0	K2=18.8
Max. of the a posteriori probability density pdf	$1.48.10^{-7}$	$1.57.10^{-7}$

This table clearly illustrates the rate of execution possible when using the modified inversion method of the invention.

Using the scenario method

The results obtained with the experimental case are set out in Fig. 6. After using the automatic procedure described above to find the optimum of the a posteriori probability density and thus to obtain the match with the actual data (from t=0 to t=300 days), a direct numerical simulation taking account of the a priori model was used up to t_f=600 days. This simulation gives an average forecast of the down hole pressure. The a priori rate of

probability ppr is then selected, in this case ppr=0.1. The method of the invention is used to identify the extreme production scenarios, the geological model remaining with this range of probability.

The constraints of iso-probability are illustrated in Fig. 7 (using Bayesian inversion mapping) in order to superpose the values corresponding to the three scenarios (optimum, maximum and minimum) in the parameter space. The location of parameters corresponding to the mini/maxi scenarios is close to the border defined by the rate of probability ppr=0.1. The numerical results are set out in table 7:

Table 7: Extreme scenarios and comparison with the optimum

	Maxi.	Optimum	Mini.
Pressure (psi)	4179	4098	4020
K1 (mD)	90.2	143.2	200.8
K2 (mD)	217.4	173.0	136.5

The uncertainty concerning the forecast of the down hole pressure at t_f=600 days is given by the difference between the maximum forecast and the minimum forecast. This demonstrates that it is possible to transpose the uncertainties pertaining to the geological model into uncertainties pertaining to production forecasts.

CLAIMS

1. A method for predicting developments during production in an underground zone containing fluids, such as a hydrocarbon reservoir, wherein it comprises the following steps:

a) an initial geological model defined by a set of parameters x̲ is constructed by integrating the data available and an inversion method is applied in order to determine the values of parameters that will allow the response of the model to be adjusted to a known production history for the said zone;

b) one or several possible scenarios of developments during production are defined and, for each of these scenarios, observed data are added to fictitious data at given future instants corresponding to hypotheses;

c) for each of the said scenarios, the parameters of the said model are adjusted to reconstruct both actual measurements from the production history and data added at future times and an inversion procedure is applied to obtain for each scenario a new set of parameters x̲ characterising a modified geological model and corresponding to the hypotheses of the scenario; and

d) for each of these modified geological models, simulations are performed to establish new production forecasts.

2. A method as claimed in claim 1, wherein scenarios corresponding to extreme forecasts are determined so as to quantify the uncertainties of forecasts produced by a simulation

3. A method as claimed in claim 1 or 2, wherein the matching of the scenarios is adjusted in a process of optimisation by a combination of a Bayesian type formalism and a gradients method.

4. A method as claimed in claim 3, wherein a gradients method is used to obtain an approximation of the a posteriori probability density.

5. A method substantially as hereinbefore described with reference to the drawings.

The Patent Office

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Application No: GB 9609487.5
Claims searched: 1 - 5

Examiner: Paul Nicholls
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Patents Act 1977
Search Report under Section 17

Databases searched:

UK Patent Office collections, including GB, EP, WO & US patent specifications, in:

UK Cl (Ed.O): G4A (AUA, AUXX)

Int Cl (Ed.6): G01V 1/00, 1/28, 1/30, 1/48, 1/50; G06F 17/00, 17/50, 19/00; G06G 7/57

Other: Online: WPI, COMPUTER, GEOLOGY

Documents considered to be relevant:

Category	Identity of document and relevant passage		Relevant to claims
A	EP 0,426,515 A1	(TOTAL PETROLES) - Whole document	-
A	US 4,340,934 A	(SEGESMAN) - Whole document	-
A	US 4,314,338 A	(SUAU and FRAWLEY) - Whole document	-
A	US 4,313,164 A	(REGAT) - Whole document	-

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